



A Statistical Method for Aggregated Wind Power Plants to Provide Secondary Frequency Control

Hu, Junjie; Ziras, Charalampos; Bindner, Henrik W.; Han, Xue

Published in:
Proceedings of 16th Wind Integration Workshop

Publication date:
2017

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Hu, J., Ziras, C., Bindner, H. W., & Han, X. (2017). A Statistical Method for Aggregated Wind Power Plants to Provide Secondary Frequency Control. In *Proceedings of 16th Wind Integration Workshop* IEEE.

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

A Statistical Method for Aggregated Wind Power Plants to Provide Secondary Frequency Control

Junjie Hu, Charalampos Ziras, Henrik W. Bindner
Department of Electrical Engineering
Technical University of Denmark
Frederiksborgvej 399, 4000 Roskilde, Denmark
Email: {junhu, chazi, hwbi}@elektro.dtu.dk

Xue Han
Energy Research Institute
National Development and Reform Commission
No. A11 Muxidi North Lane, Beijing, China
Email: xueh88@hotmail.com

Abstract—The increasing penetration of wind power brings significant challenges to power system operators due to the wind's inherent uncertainty and variability. Traditionally, power plants and more recently demand response have been used to balance the power system. However, the use of wind power as a balancing-power source has also been investigated, especially for wind power dominated power systems such as Denmark. The main drawback is that wind power must be curtailed by setting a lower operating point, in order to offer upward regulation. We propose a statistical approach to reduce wind power curtailment for aggregated wind power plants providing secondary frequency control (SFC) to the power system. By using historical SFC signals and wind speed data, we calculate metrics for the reserve provision error as a function of the scheduled wind power. We show that wind curtailment can be significantly reduced compared to a robust and conservative scheduling, by appropriately choosing a higher operating point based on the error's expected value and the service error requirement.

I. INTRODUCTION

In power systems, renewable energy such as wind power is widely adopted to reduce greenhouse gas emissions. However, the increasing development of wind power brings operational challenges into the power systems due to its intermittent production. To cope with these challenges, power system operators currently rely on conventional dispatchable power plants, as well as demand response technologies, to ensure the stable and reliable power system operation. As variable generation resources displace conventional generation units, there is a big concern about the sufficient frequency service provision, i.e. active power balancing resources, in the near future. Although demand response is highly promoted to cope with this issue, many factors such as the controllability to the demand side devices and the acceptance by the end-users make their real application challenging. Thus, recently, it is noticed that power system operators are starting to consider wind energy as a frequency service provider, since wind turbines have the capability to rapidly track power commands [1]–[4].

However, there exist many technological and economic challenges in terms of using wind power for frequency regulation. For example, in order to offer frequency reserves with WPPs, an economic trade-off design between spot energy market participation and frequency reserve market participation is required [5]. Furthermore, this means that the control strategies of WPPs will change from maximizing power output to power tracking [6]. In this study, we focus on one of these key challenges by addressing the WPP's power

setting near the real time operation. In general, two phases are needed for frequency service provision in the deregulated electricity market: reserve phase and control phase. There is a variety of names used for frequency services, depending on the individual power system. In this work, primary reserve, secondary reserve, and manual reserve, corresponding to primary frequency control, secondary frequency control (SFC) and regulating power, respectively, are used to reflect the system needs for power balance at different time scales [7]. Secondary reserve consists of upward reserve and downward reserve, is symmetrical, and its regulation is done automatically by the plant, which responds to signals received from the power system operator, typically every 2 – 4 seconds.

Recent work [8]–[10] has shown that wind turbines can effectively provide SFC by tracking power signals sent by the system operator. In [8], a wind turbine's control system is developed to provide SFC. By working in de-rating mode, the control system aims at tracking an absolute power command sent from the system operator. The control system receives and tracks the automatic generation control (AGC) signal, which is added to the power dispatch schedule. The simulation results indicated that as long as significant wind resource is available, a wind turbine can control its power output to track the AGC signal very rapidly and accurately. Furthermore, the work also evaluates the wind turbine's performance using the new CAISO¹ and PJM² performance metrics. In [9], a wind farm is investigated to provide SFC where a model-based receding horizon approach is used. The study considers wake effects within the wind farm and the controller is implemented in a large eddy simulation model. Furthermore, the controller of [10] is tested on two types of regulation signals, 'RegA' and 'RegD', obtained from PJM. The results showed that the controlled wind farm performs well when responding to RegD signals, while surpassing the control threshold in response to RegA signals.

While previous work [8]–[10] demonstrated that wind power can be used to provide SFC, it is also observed that the assumptions used in the literature can be improved. For example, the regulation signal is normally assumed to be constant in a relatively long time window, and the mean wind speed is used in the simulations to illustrate the control

¹The California independent system operator.

²PJM is a regional transmission organization that coordinates the whole-sale electricity in all or parts of 13 US states and the District of Columbia.

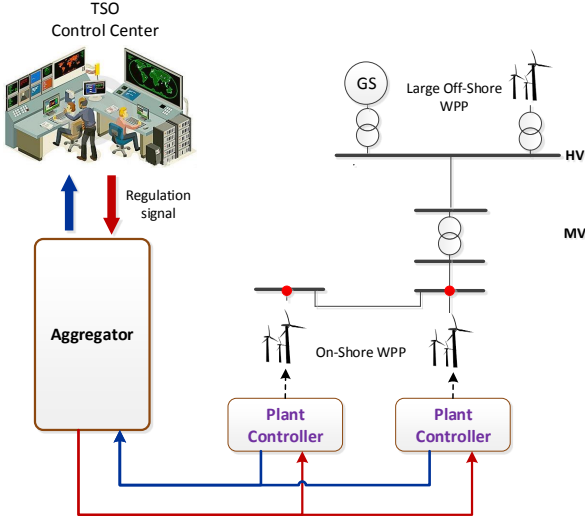


Fig. 1: Overview of actors in a schematic power system

performance, which cannot reflect the real dynamics. Most importantly, the goal of these studies is not to minimize wind power curtailment. The main contribution of this paper is to present a statistical but generic method to minimize wind power curtailment for aggregated WPPs providing SFC. The statistic method uses the historical frequency regulation signal to optimize the setting power of individual WPP based on the very short-term predicted wind power and the SFC performance requirements of the European network of transmission system operators for electricity (ENTSOE). The predicted wind power will consider the variation of wind power inside the short term period and therefore the dynamics of the WPPs can be studied when providing SFC. In addition, as discussed in [11], the aggregated power of multiple wind farms would bring additional benefits such as reducing the overall variability in terms of wind resources, this feature would help their provision of SFC, which will be initially explored in this study.

II. SYSTEM ARCHITECTURE AND ASSUMPTIONS

As shown in Fig. 1, an aggregator is proposed to coordinate the WPPs power output in order to provide frequency regulation services to the transmission system operator (TSO). We assume that the reserve capacity P_{res} is symmetrical and hourly constant throughout a period of 24 hours. The aggregator receives the normalized regulation signal $r_t \in [-1, 1]$ from the TSO every t_c seconds and must respond to r_t by changing the WPPs output. The power setting refers to a constant aggregated power reference sent to the TSO every t_{sch} seconds, and corresponds to the target WPPs power for $r_t = 0$. We refer to each period of t_{sch} as the scheduling period and for this study $t_{\text{sch}} = 600$ s. The aggregated wind power output must be regulated as

$$P_{\text{wpp},t} = P_{\text{sch},t} + r_t P_{\text{res}} \quad (1)$$

A WPP can offer frequency regulation services by curtailing its power output, so that it is able to provide both upward and downward regulation. We assume that the reserve capacity bidding was done in a robust manner, i.e. the WPPs

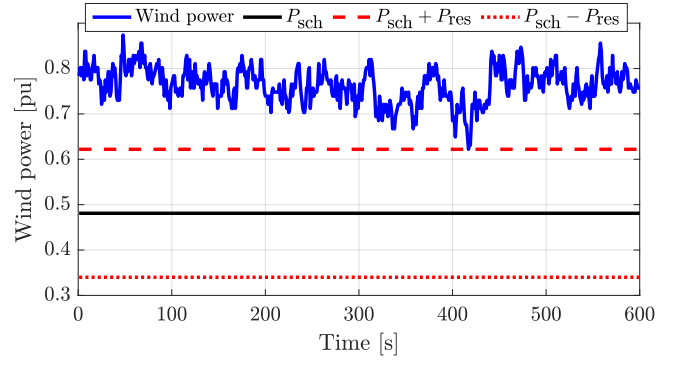


Fig. 2: Short-term scheduling of a WPP for robust service provision

are able to fully meet the reserve provision requirements under any realized wind speed scenario, if enough wind power is curtailed. However, setting P_{sch} so that any r_t can be followed under any possible wind speed scenario is a very conservative approach, which can lead to a significant amount of wind power curtailment.

Fig. 2 shows how P_{sch} would be chosen, so that any r_t would be followed at every time step. It is also reasonable to assume that near-to-second prediction of the wind speed for a period of 5 – 10 minutes is unrealistic, therefore wind-speed uncertainty must also be considered. Under a robust short-term scheduling, P_{sch} would be chosen by considering the combined worst-case realizations of the wind speed and reserve request, leading to a very conservative scheduling; as illustrated in the figure, the black line shows P_{sch} , considering only one wind scenario.

We propose a statistically-based short-term online scheduling approach for an aggregator, which utilizes the statistical properties of the secondary frequency regulation signal, the performance margin of the provided service and wind speed historical data. Such a scheduling method can be used by an aggregator in order to choose a P_{sch} which optimizes its profits, minimizes the imbalance cost due to the difference between P_{sch} and the day-ahead (DA) schedule or to minimize wind-power curtailment. Without loss of generality, we will use our approach to study the potential reduction in wind-power curtailment, while meeting the service provision requirements. Considering all these factors, the assumptions and system setup can be summarized as follows:

- At every scheduling period, the aggregator calculates the maximum P_{sch} for the following t_{sch} seconds, while considering the service requirements.
- P_{res} is known and has been set in a robust manner, guaranteeing full service delivery at the worst case.
- The aggregator predicts multiple wind power scenarios for the following t_{sch} seconds. In this study, we assume perfect forecast of the average wind speed and we add noise terms sampled from historical wind data, to generate the multiple wind power scenarios.
- The regulation signal is sent every t_c seconds.

III. STATISTICAL CONTROLLER AT AGGREGATOR LEVEL

A. Control performance index

Achieving 100% performance accuracy when providing frequency regulation services is almost practically impossible, due to various reasons such as communications delays, measurement errors, control granularity, and units dynamics. For this reason, system operators define performance indices to assess SFC control performance. In general, service verification can be categorized in two main schemes. The first one is pay as performance, as implemented by PJM, where each service provider is remunerated based on a number of performance criteria, one of which is tracking accuracy. The second is to establish performance requirements and maximum allowed errors, such as the performance index on secondary control by the Swiss TSO, Swissgrid [12]. In the case of Swissgrid, the pre-qualification process requires a minimum accuracy of 1%, calculated by the following formula

$$\frac{\sum_{t=1}^{t_{\text{tot}}} |P_{\text{diff},t}| t_c}{2P_{\text{res}} t_{\text{tot}}} \cdot 100\% \leq 1\% \quad (2)$$

P_{diff} is the power value in excess of the tracking tolerance, which is equal to $\pm 5\%$ P_{res} around the power reference, t_{tot} is the total provision time, and t_c is the sampling time. This formula is used by the online decision system to calculate the error over the 10 minutes control interval.

B. Wind power uncertainty modelling

The following equation is used to calculate the aggregated WPP's power from the estimated equivalent wind speed

$$P = \begin{cases} 0, & \text{if } V \leq V_{\text{in}} \text{ or } V \geq V_{\text{out}} \\ \frac{V - V_{\text{in}}}{V_r - V_{\text{in}}} P_N, & \text{if } V_{\text{in}} \leq V \leq V_r \\ P_N, & \text{if } V_r \leq V \leq V_{\text{out}}, \end{cases} \quad (3)$$

where V , V_{in} , V_r and V_{out} are the wind speed, cut-in speed, rated speed, and cut-out speed respectively. P represents the available power and P_N denotes the rated power.

As described in Section II, it is assumed that the average 10 minutes wind power over a period of t_{sch} seconds can be perfectly predicted. Based on available historical data, we observed that the per-second variation of wind power around the 10 minutes average value is normally distributed. Moreover, we observed a strong auto-correlation of the variation, as is evident in Fig. 3 for the wind scenario used in the previous example. In this study, we randomly select the wind power variation from historical samples and then add them on the (known) 10 minutes wind power.

C. Statistical online scheduling method

With the predicted wind power for each plant, the aggregator will choose the power schedule P_{sch} of each WPP for the following control period, in order to provide the committed reserve capacity P_{res} within the service performance margin. In our example we consider a robust day-ahead commitment, and the aggregator tries to minimize the wind curtailment, i.e., the reserve made day-ahead can be guaranteed. As shown in Fig. 4, the controller updates the base power setting P_{sch} every 10 minutes.

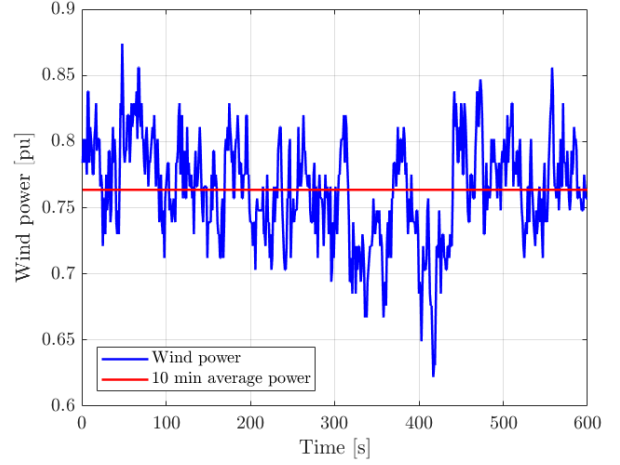


Fig. 3: Per second wind power and 10 min average power of a WPP

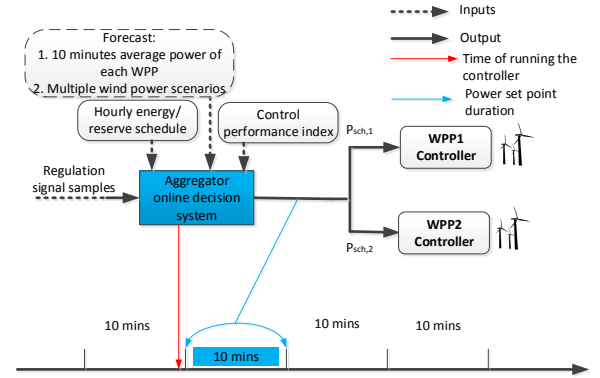


Fig. 4: The aggregator online scheduling system

To illustrate the proposed statistical scheduling method, we consider the case where the aggregator controls only one WPP. We calculate the control provision error for various P_{sch} values and a large number of scenarios; we consider a number of N wind power scenarios and a number of M historical regulation signal samples. A minimum value of the base power P_{sch} is chosen, such that it corresponds to a robust scheduling which guarantees 100% reserve provision under any wind and regulation signal realization. Then this value is increased by small steps, whose total number is equal to D . For each value of P_{sch} , $N \cdot M$ control errors are calculated by using (2). We then calculate various statistical metrics based on which the aggregator can select the power schedule; the largest value of P_{sch} which respects the specified criteria is then selected.

In the case of more than one WPPs, the aggregator can utilize the other WPPs when one or more WPPs are not able to follow their set-points. Again, the P_{sch} values for all WPPs are increased in small steps, but the aggregated control error is calculated by considering the capabilities of all WPPs. In that case, different wind scenarios must be generated for each WPP, whereas the regulation signal scenarios are common. The desired statistical metrics are then calculated for each combination of $P_{\text{sch},i}$ values (i is the index of the WPPs),

and a set of $P_{sch,i}$ values is chosen, such that the criteria are met.

IV. RESULTS

In this section we will use real wind speed measurement data of two WPPs as well as historical regulation signals to illustrate the proposed statistical scheduling method. For the wind power calculation, the cut-in speed, rated speed and cut-off speed are 3 m/s, 13 m/s, and 25 m/s, respectively. The average pu and in MW power of WPP i is denoted by $P_{av,i}^{pu}$ and $P_{av,i}$ respectively. Two case studies are presented in this section; in the first one WPP is used by the aggregator and in the second the aggregator controls two WPPs. The relevant parameters of the two WPPs are:

- $P_{N,1} = 15$ MW and $P_{N,2} = 30$ MW; note that the available second-based wind speed at the WPP level corresponds to real measurements, but the size of the two WPP plants is assumed here.
- $P_{av,1}^{pu} = 0.7298$ pu and $P_{av,1} = 10.9465$ MW. $P_{av,2}^{pu} = 0.6796$ pu and $P_{av,2} = 20.3889$ MW.
- The reserve capacity is equal to 20% of the mean power. Thus, $P_{res,1} = 2.1893$ MW and $P_{res,2} = 4.0778$ MW.
- The power increment of both WPPs is equal to 0.01 pu.

A. Case Study I: One WPP

In the first case study we consider the first WPP. As discussed, in real time the control purpose is to increase P_{sch} , i.e., to increase the bulk power supply and meanwhile ensure reserve provision.

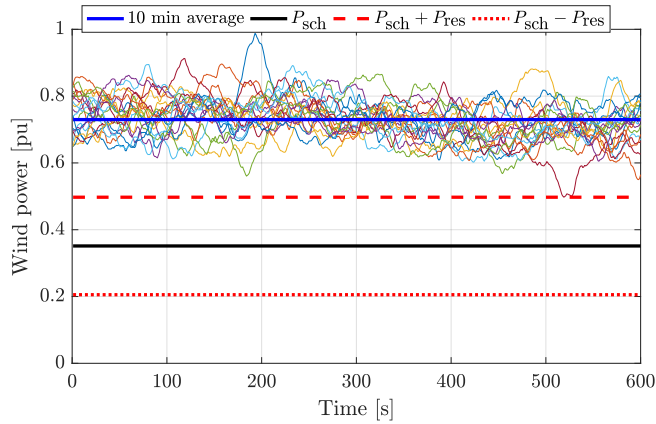


Fig. 5: 20 wind power realizations. The black line represents the robust scheduled power and the blue line shows the (perfectly) predicted average wind power

Fig. 5 shows 20 possible wind power scenarios as well as the minimum value of P_{sch} to guarantee robust reserve provision; in this case, the scheduled power value is equal to 0.351 pu or 5.2705 MW. For the regulation signal, the RegD signal of PJM³ is used [13]. In Fig. 6 an hourly sample of the RegD signal is shown. Note that RegD is sent every 2 seconds, but we evaluate the control performance per second ($t_c = 1$ s). We randomly selected 1000 historical RegD signal samples for the simulation.

³We use this data as a SFC signal because SFC data from the ENTSOE area was not publicly available; thus the RegD signal is used since the regulation signals used in PJM and ENTSOE area share similarities.

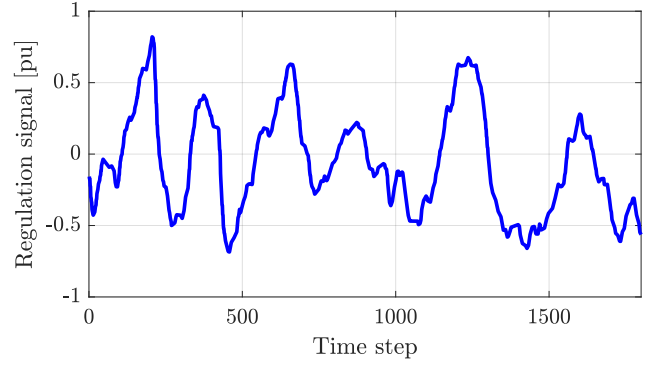


Fig. 6: A 1 hour RegD regulation signal sample

We calculate the SFC control error for $N \cdot M = 1000 \cdot 20 = 20000$ scenarios for each value of P_{sch} by setting P_{sch} equal to the minimum (robust) value and then increasing the base power with a 0.01 pu step. Next, as shown in Fig. 7, we calculate 4 different statistical metrics for the error distributions for each P_{sch} value. Notice that the errors may take very large values in some scenarios, as indicated by the worst-case errors, but the expected values are considerably smaller.

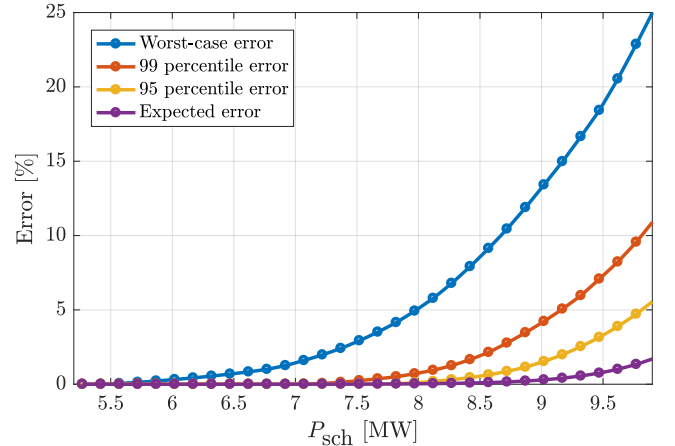


Fig. 7: 4 Different statistical metrics of the SFC error as a function of P_{sch}

From this graph, the aggregator is able to select the WPP's P_{sch} according to its control objective. For instance, if the objective is to achieve an expected SFC error of 1%, P_{sch} would be set equal to 9.62 MW. The aggregator could also select P_{sch} based on other error metrics such as the 95 percentile error. The simulation requires only a few seconds to execute, performed in Matlab version 2016a with a central processing unit of Intel Core i7, 2.60 GHz, which is fast enough for the online decision requirements. Using the same procedure, we found that P_{sch} for the second WPP can be increased from 12.574 MW (robust case) to 18.34 MW for an expected error of 1%.

B. Case Study II: Two WPPs

In this subsection we consider the joint operation of the 2 WPPs, we calculate the total SFC errors and we derive a fit for the expected values of the errors, as shown in Fig. 8; by

using this graph, the aggregator can use different combinations of $P_{sch,1}$ and $P_{sch,2}$ to achieve an expected SFC error equal to 1%. The maximum total scheduled power is equal to 30 MW and is achieved by selecting $P_{sch,1} = 8.4205$ MW and $P_{sch,2} = 21.574$ MW. It is interesting to note that the total power achieved by controlling the 2 WPPs separately is equal to 28 MW. Therefore, the joint control results in a considerable reduction of the total wind power curtailment. This performance improvement was expected, since in most scenarios the worst cases of the wind speed of the 2 WPPs do not coincide (assuming no correlation between the fast wind variations of the WPPs added on top of the predicted average wind speeds) and the total control errors can be reduced.

However, the computational time increases a lot compared to the one WPP case since the total number of the scenarios increase considerably. Overall, the simulation takes 40 seconds, but this time can be significantly reduced. For instance, many power combinations (close to the robust values) result in very low errors and the initial P_{sch} values can be increased, reducing the total number of the scenarios. Furthermore, parallel computing can be utilized, which can substantially decrease the computational times (our focus was not on the computational aspects). Nevertheless, if a large number of WPPs are controlled, scenario reduction methods will be necessary.

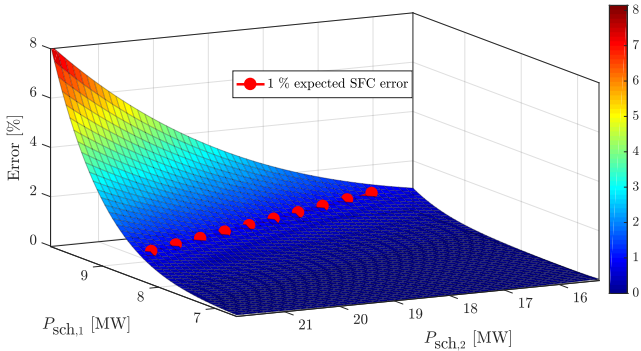


Fig. 8: Fitting of the average SFC errors as a function $P_{sch,1}$ and $P_{sch,2}$. The red points show power setting combinations resulting in expected errors equal to 1%

V. CONCLUSION AND DISCUSSION

In this paper we proposed a method to minimize the wind power curtailment of an aggregator of WPPs offering secondary frequency control. The method relies on using historical frequency regulation signal data and wind speed scenarios, in order to calculate the reserve provision errors for different WPP power set-points. By using such a statistical approach, we showed that the power set-points can be significantly increased, compared to a fully robust scheduling, which guarantees service delivery under any realization of the wind speed and the regulation signal. As a result, the economic performance of the WPPs offering frequency control can be greatly improved, while respecting the expectations of the service performance requirements.

Our results are promising but several simplifications were made. For example, the aggregated WPP models result in

relatively small errors compared to the detailed models, but as discussed in [14], the active power errors are close to 3% for low wind speeds and smaller than 6% for speeds close to the rated values. In our future work we will investigate the effect of such errors, as well as the effect of imperfect forecasts of the average wind speed. Furthermore, we plan to validate the proposed method using a more detailed WPP model which will include the wind turbine's controllers and we will also consider more factors, such as communication delays. Finally, we will consider correlation of the wind speed scenarios between different WPPs, which is likely when they are closely located.

ACKNOWLEDGMENT

The authors would like to thank colleagues Mufit Altin and Anca D. Hansen from DTU Wind Energy for the valuable discussions. This work is supported by Energinet.dk's ForkEl project Replan (Ancillary services from renewable power plants, project number: 12347). <http://www.replanproject.dk/>.

REFERENCES

- [1] N. Miller, K. Clark, and M. Shao, "Frequency responsive wind plant controls: Impacts on grid performance," in *Power and Energy Society General Meeting, 2011 IEEE*, pp. 1–8, IEEE, 2011.
- [2] M. Altin, A. Hansen, N. Cutululis, H. Bindner, F. Iov, and R. Olsen, "Ancillary Services from Renewable Power Plants – RePlan Project perspective," *Proceedings of the 14th Wind Integration Workshop, Bruxelles, Belgium*, 2015.
- [3] A. D. Hansen, M. Altin, and F. Iov, "Provision of enhanced ancillary services from wind power plants – examples and challenges," *Renewable Energy*, vol. 97, pp. 8 – 18, 2016.
- [4] J. Aho, A. Buckspan, and J. H. Laks, "A tutorial of wind turbine control for supporting grid frequency through active power control," *Proc. of the American Control Conference*, no. March, pp. 3120–3131, 2012.
- [5] T. Soares, P. Pinson, T. V. Jensen, and H. Morais, "Optimal offering strategies for wind power in energy and primary reserve markets," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 3, pp. 1036–1045, 2016.
- [6] J. Aho, A. Buckspan, L. Y. Pao, and P. A. Fleming, "An Active Power Control System for Wind Turbines Capable of Primary and Secondary Frequency Control for Supporting Grid Reliability," *AIAA/ASME Wind Symposium*, no. January, pp. 1–13, 2013.
- [7] Energinet.dk, "Ancillary services to be delivered in Denmark tender conditions," *Technical report*, 2012.
- [8] J. Aho, L. Y. Pao, P. Fleming, and E. Ela, "Controlling Wind Turbines for Secondary Frequency Regulation : An Analysis of AGC Capabilities Under New Performance Based Compensation Policy," *13th Wind Integration Workshop*, no. February 2015, 2014.
- [9] C. R. Shapiro, P. Bauweraerts, J. Meyers, C. Meneveau, and D. F. Gayme, "Model-based receding horizon control of wind farms for secondary frequency regulation," *Wind Energy*, March 2017.
- [10] C. R. Shapiro, J. Meyers, C. Meneveau, and D. F. Gayme, "Wind farms providing secondary frequency regulation: Evaluating the performance of model-based receding horizon control," *Journal of Physics: Conference Series*, vol. 753, p. 052012, 2016.
- [11] Z. Lu, X. Ye, Y. Qiao, and Y. Min, "Initial exploration of wind farm cluster hierarchical coordinated dispatch based on virtual power generator concept," *CSEE Journal of Power and Energy Systems*, vol. 1, pp. 62–67, June 2015.
- [12] D. Schlipf, M. Scherer, and M. Haller, "Swissgrid test for secondary control capability," *Technical report*, 2012.
- [13] PJM, "Ancillary services," <http://www.pjm.com/markets-and-operations/ancillary-services.aspx>.
- [14] A. D. Hansen, M. Altin, and N. A. Cutululis, "Modelling of wind power plant controller, wind speed time series, aggregation and sample results," *DTU Wind Energy E-0080*, January 2015.